Sensor Applications

A Transform domain Approach for the Compression of Fetal Phonocardiogram Signal

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Abstract—In this letter, a transform-based methodology is presented for the compression of fetal Phonocardiogram (fPCG) signal. Transform techniques such as Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), and Fast Walsh Hadamard Transform (FWHT) are applied for the decomposition of fPCG signal and a comparative study on the performance of different transforms is made in terms of measures such as Compression ratio (CPR), Percent root mean square difference (PRD), Mean square error (MSE), Quality Score (QS), and Signal-to-noise ratio (SNR). The simulation results reveal the effectiveness of the transform techniques in fPCG signal compression. In comparison, it is observed that FWHT gives a better CPR while DWT yields good fidelity parameters with comparable CPR.

Index Terms—PCG, Compression, DCT, DWT, FWHT.

I. INTRODUCTION

Cardiovascular diseases (CVDs) are reported to be the world's leading cause of death, and especially in case of pregnancy-related deaths, 26.5% is reported due to congenial heart defects [1]. It is also reported that more than 80% of maternal deaths and fetal distress can be avoided by strengthening the maternal health care [2]. As pregnant women are periodically demanded to monitor the variations of fetal heart rate (FHR) and consult doctors, telemedicine (TM) systems can play a vital role in improving maternal health care [3]. TM systems help to communicate patient health information and medical reports to the physicians through electronic information benefitting people who live in distant, rural, or remote areas and not having access to timely, good quality and specialty medical care for early diagnosis and treatment [4]. PCG signal is an important diagnostic tool for detecting CVDs. For monitoring FHR, fetal PCG (fPCG) signals are widely used nowadays. In order to avoid frequent travel of pregnant women, fPCG signals can be recorded and transmitted to medical specialists for diagnosis and treatment using TM systems. For better diagnostic information, the fPCG signals need to be recorded for a long time with a good sampling rate and resolution, which demands a large memory storage capacity, long transmission time, and large bandwidth [5]. Hence to reduce the storage capacity and speed up the transmission, it is necessary to compress the PCG signal. While compressing, it should be taken care of that the signal is not degraded and all its important aspects are preserved because it contains vital diagnostic information for analyzing heart defects. In general, fast Fourier transform (FFT) [6], DCT [7], and DWT [8] [9] are the different compression techniques applied for signal compression. In this work, we have used FWHT for fPCG signal compression. It is selected as it enables fast computation of coefficients needed for compression and requires less storage space [10]. It stores only those sequence coefficients having large magnitudes and allows fast signal reconstruction. Its performance is evaluated in terms of CPR, PRD, MSE, QS, and SNR and compared with DCT and DWT transformation techniques. The rest of this letter is structured as follows. Section 2 presents the different types of techniques applicable to PCG signal compression. In Section 3, the proposed methodology for signal compression is described. The results are discussed in Section 4, and the conclusions are presented in the last section.

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II. TECHNIQUES FOR PCG SIGNAL COMPRESSION

DCT, DWT, and FWHT are different transformation techniques used to compress the PCG signal and are described in the following subsections.

A. Discrete Cosine Transform

DCT is calculated using the FFT algorithm, and it gives higher weight to low-pass coefficients than high-pass coefficients. It provides optimal performance in compressing standard signals, which have a high correlation in adjacent samples [11]. DCT based compression involves four steps: (i) partition the signal into consecutive blocks (ii) DCT computation for each block (iii) apply bisection algorithm to obtain the threshold values from the DCT coefficients (iv) encode the quantized DCT coefficients [12] [13]. DCT is defined as in (1) [14]

$$y(n) = \sum_{i=0}^{N-1} a(n)\cos\left[\frac{\pi n}{2N}(2i+1)\right] x(i) \tag{1}$$

and the inverse IDCT is defined as in (2)

$$x(i) = \sum_{n=0}^{N-1} a(n)\cos\left[\frac{\pi n}{2N}(2i+1)\right] y(n) \tag{2}$$

where, $i = 0, 1, , ..., (N-1)$ and $n = 0, 1, ..., (N-1)$, N is the length of the signal, and

$$a(n) = \begin{cases} \sqrt{\frac{1}{N}}, & n = 0 \\ \sqrt{\frac{2}{N}}, & n \neq 0 \end{cases} \tag{3}$$

B. Discrete Wavelet Transform

DWT has emerged as a powerful and robust tool for analyzing and extracting information from non-stationary signals like PCG signals. It gives the multi-resolution decomposition of PCG signal [11]. DWT based compression involves six steps: (i) decomposition into six levels using Daubechies 4 (db4) wavelet filters [15] which provides the higher SNR for all types of fPCG signals and found effective in maintaining consistent increase in compression ratio with increase in PRD value out of other available wavelets (ii) threshold the transformed coefficients using bisection algorithm (iii) iterative computation until the user-specified percentage predefined root mean square difference (UPRD) is achieved (iv) creation of binary lookup table (LUT) using threshold values (v) position mapping using LUT (vi) encoding by Huffman coding [10].

C. Fast Walsh Hadamard Transform

FWHT is an effective technique to approximate the Walsh–Hadamard Transform (WHT), which converts a time-domain signal into a frequency domain [16]. It decomposes the signal into a series of orthogonal, rectangular waveforms called Walsh functions, which has only two values -1 and/or +1 [17]. Threshold is computed using bisection algorithm which considers the maximum and minimum amplitude of the fPCG signal to return a root value which lies in the bound. FWHT is a faster version of the WHT, which takes less time to compute and requires less storage space. It uses only real addition and subtraction, while FFT uses complex values. For any signal $x(n)$ of size N, FWHT and inverse FWHT are defined as follows [18]:

$$y(n) = \frac{1}{\mathrm{N}} \sum_{j=0}^{\mathrm{N}-1} x(n)\mathrm{WAL}(n, j) \tag{4}$$

and

$$x(n) = \sum_{j=0}^{\mathrm{N}-1} y(n)\mathrm{WAL}(n, j) \tag{5}$$

where, $j = 0, 1, ...\mathrm{N}-1$ and $\mathrm{WAL}(n, j)$ are the Walsh functions. Similar to FFT's Cooley-Tukey algorithm, the two sets of $\frac{\mathrm{N}}{2}$ elements obtained by decomposing N elements, are then combined to form FWHT, using a butterfly structure [19].

III. METHODOLOGY FOR PCG SIGNAL COMPRESSION

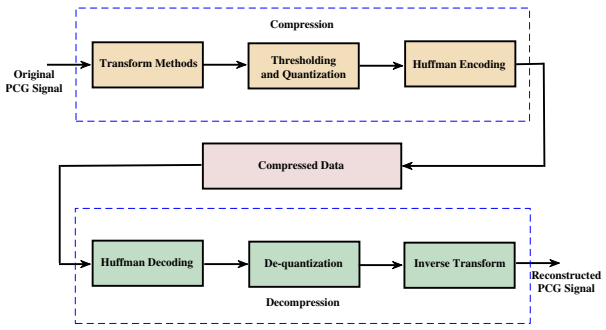

Fig. 1. Steps for PCG signal compression

Fig. 1 shows the various steps involved in PCG signal compression. In order to compress the signal and to obtain the coefficients, transform techniques such as DCT, DWT, and FWHT are used in this work. Once the coefficients are obtained suitable threshold rule is applied, and then quantization is done. After this to perform actual compression, entropy encoding (Huffman) technique is applied [20] [21]. The obtained compressed signal can be stored for later use or transmitted for diagnosis and treatment. Further, at the receiver end, the PCG signal is reconstructed from compressed PCG data by applying the inverse compression method, i,e., decoding, followed by de-quantization. The performance analysis of the different transform techniques is evaluated using various performance measures such as CPR, MSE, QS, and SNR. CPR is defined as CPR=$\frac{\mathrm{N}_0}{\mathrm{N}_1}$ where, N_0 and N_1 indicates the data size before and after compression. PRD indicates the distortion measure of the reconstructed PCG signal. A high CPR and a low PRD corresponds to a good compression performance. MSE measures the average squared difference between the estimated value and the actual value. MSE and PRD are evaluated as in (6) and (7), respectively.

$$\mathrm{MSE} = \frac{1}{\mathrm{N}} \sum_{n=1}^{\mathrm{N}} (x_n - \hat{x}_n)^2 \tag{6}$$

$$\mathrm{PRD} = \sqrt{\frac{\sum_{n=1}^{\mathrm{N}} (x_n - \hat{x}_n)^2}{\sum_{n=1}^{\mathrm{N}} x_n^2}} \times 100 \tag{7}$$

where, x_n is the n^{th} sample in the original PCG signal, and $\hat{x}_n$ indicates the corresponding reconstructed signal of sample length N. QS is defined as QS = CPR/PRD. A high QS value indicates good performance. SNR indicates the amount of noise present in the PCG signal due to compression and is expressed as in (8)

$$\mathrm{SNR} = 10log\left[\frac{\sum_{n=1}^{\mathrm{N}} x_n^2}{\sum_{n=1}^{\mathrm{N}} (x_n - \hat{x}_n)^2}\right] \tag{8}$$

IV. RESULTS AND DISCUSSION

In this work, we have used 26 fPCG signals (taken from different pregnant women aged between 25 and 35 years) obtained from publicly available fetal PCG database (fpcgdb)[1] [22].

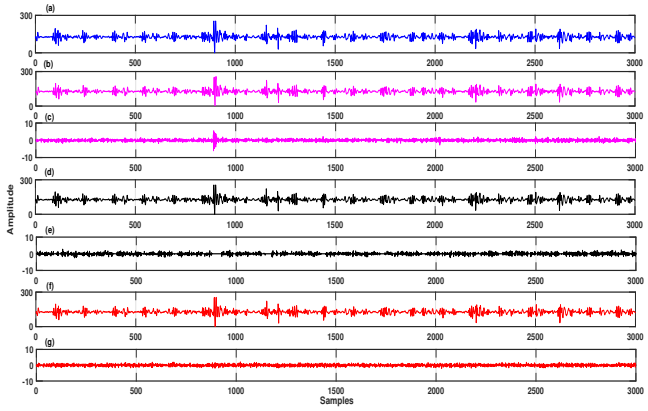

Fig. 2. (a) Original fetal PCG signal (fPCG_p01_GW_36) (b) Reconstructed signal (CPR=5.42) using DCT (c) Error signal (MSE=0.43) using DCT (d) Reconstructed signal (CPR=5.85) using DWT (e) Error signal (MSE=0.42) using DWT (f) Reconstructed signal (CPR=27.49) using FWHT (g) Error signal (MSE=0.42) using FWHT.

[1] https://physionet.org/content/fpcgdb/1.0.0/

TABLE 1. Compression performance of fetal PCG signals using DCT

	UPRD = 0.5				UPRD = 1.0				UPRD = 1.5				UPRD = 2.0			
	CPR	**MSE**	**QS**	**SNR**	**CPR**	**MSE**	**QS**	**SNR**	**CPR**	**MSE**	**QS**	**SNR**	**CPR**	**MSE**	**QS**	**SNR**
fPCG_p01_GW_36	5.42	0.43	10.60	66.13	5.57	1.78	5.37	51.97	5.71	3.81	3.75	44.35	5.83	6.77	2.88	38.62
fPCG_p02_GW_31	5.39	0.44	10.39	62.69	5.58	1.85	5.24	48.35	5.78	3.81	3.79	41.14	6.05	6.78	2.97	35.38
fPCG_p04_GW_38	5.42	0.39	10.96	60.72	5.65	1.80	5.36	45.62	5.84	3.66	3.90	38.57	6.09	6.81	2.98	32.35
fPCG_p05_GW_34	5.55	0.40	11.01	57.04	5.86	1.68	5.72	42.91	6.09	3.68	4.02	35.08	6.28	6.58	3.10	29.27
fPCG_p07_GW_38	5.59	0.41	11.00	55.18	5.90	1.64	5.83	41.39	6.13	3.58	4.10	33.59	6.38	6.48	3.17	27.66
fPCG_p10_GW_36	5.53	0.40	11.18	57.48	5.80	1.71	5.66	42.95	6.06	3.68	4.03	35.27	6.25	6.73	3.07	29.24
fPCG_p11_GW_37	5.51	0.41	11.00	60.36	5.75	1.68	5.67	46.26	5.98	3.76	3.94	38.22	6.14	6.64	3.05	32.54
fPCG_p12_GW_39	5.37	0.39	10.89	61.12	5.57	1.83	5.27	45.89	5.72	3.65	3.83	38.99	5.91	6.92	2.87	32.60
fPCG_p21_GW_39	5.50	0.41	10.83	66.34	5.70	1.59	5.75	53.00	5.89	3.62	3.94	44.79	6.08	6.52	3.03	38.90
fPCG_p25_GW_37	5.37	0.42	10.49	60.76	5.61	1.91	5.16	45.68	5.79	3.59	3.88	39.38	6.06	6.72	2.97	33.13
Average	**5.46**	**0.41**	**10.83**	**60.78**	**5.69**	**1.74**	**5.50**	**46.40**	**5.89**	**3.68**	**3.91**	**38.93**	**6.10**	**6.69**	**3.00**	**32.96**

TABLE 2. Compression performance of fetal PCG signals using DWT

	UPRD = 0.5				UPRD = 1.0				UPRD = 1.5				UPRD = 2.0			
	CPR	**MSE**	**QS**	**SNR**	**CPR**	**MSE**	**QS**	**SNR**	**CPR**	**MSE**	**QS**	**SNR**	**CPR**	**MSE**	**QS**	**SNR**
fPCG_p01_GW_36	5.85	0.42	11.54	66.30	6.07	1.64	6.07	52.75	6.23	3.73	4.14	44.57	6.44	7.15	3.09	38.07
fPCG_p02_GW_31	6.07	0.42	11.93	63.09	6.38	1.68	6.30	49.34	6.62	3.67	4.41	41.50	6.78	6.62	3.37	35.62
fPCG_p04_GW_38	5.83	0.43	11.33	59.93	6.08	1.82	5.75	45.54	6.22	3.69	4.13	38.46	6.47	7.11	3.09	31.92
fPCG_p05_GW_34	5.94	0.42	11.54	56.64	6.19	1.65	6.10	43.07	6.45	3.67	4.26	35.10	6.74	6.93	3.24	28.75
fPCG_p07_GW_38	6.07	0.42	11.83	54.98	6.53	1.78	6.20	40.57	6.85	3.59	4.57	33.57	7.30	6.37	3.66	27.83
fPCG_p10_GW_36	6.27	0.39	12.72	57.57	6.75	1.62	6.75	43.43	7.11	3.67	4.74	35.31	7.59	6.66	3.75	29.35
fPCG_p11_GW_37	5.88	0.40	11.89	60.62	6.13	1.66	6.08	46.36	6.34	3.68	4.23	38.45	6.60	6.94	3.20	32.10
fPCG_p12_GW_39	5.78	0.40	11.63	60.97	6.06	1.77	5.82	46.22	6.32	3.71	4.20	38.84	6.74	7.05	3.25	32.42
fPCG_p21_GW_39	5.96	0.39	12.08	66.96	6.21	1.68	6.09	52.41	6.43	3.64	4.29	44.73	6.69	6.75	3.28	38.56
fPCG_p25_GW_37	5.86	0.43	11.31	60.49	6.16	1.91	5.66	45.68	6.36	3.66	4.23	39.19	6.70	6.84	3.25	32.95
Average	**5.95**	**0.41**	**11.78**	**60.75**	**6.25**	**1.72**	**6.08**	**46.53**	**6.49**	**3.67**	**4.32**	**38.97**	**6.80**	**6.84**	**3.31**	**32.75**

TABLE 3. Compression performance of fetal PCG signals using FWHT

	UPRD = 0.5				UPRD = 1.0				UPRD = 1.5				UPRD = 2.0			
	CPR	**MSE**	**QS**	**SNR**	**CPR**	**MSE**	**QS**	**SNR**	**CPR**	**MSE**	**QS**	**SNR**	**CPR**	**MSE**	**QS**	**SNR**
fPCG_p01_GW_36	27.49	0.42	54.46	66.40	28.08	1.93	25.94	51.15	28.72	3.70	19.18	44.66	29.84	6.60	14.92	38.87
fPCG_p02_GW_31	42.89	0.40	86.31	63.57	44.02	1.94	40.39	47.87	46.40	3.67	31.00	41.54	50.64	7.11	24.31	34.92
fPCG_p04_GW_38	42.00	0.43	81.56	59.92	42.74	1.81	40.55	45.61	44.49	3.71	29.47	38.41	47.95	6.81	23.46	32.35
fPCG_p05_GW_34	43.86	0.40	87.77	57.25	44.67	1.94	40.63	41.48	46.95	3.63	31.20	35.20	51.33	7.05	24.50	28.59
fPCG_p07_GW_38	43.12	0.39	87.06	55.69	43.14	1.92	39.37	39.81	45.94	3.68	30.31	33.32	48.62	6.56	24.02	27.54
fPCG_p10_GW_36	37.12	0.40	74.82	57.45	36.83	1.63	36.79	43.41	37.62	3.68	25.02	35.28	39.14	7.02	18.85	28.82
fPCG_p11_GW_37	39.10	0.41	77.44	60.20	40.64	1.89	37.84	45.11	41.45	3.73	27.46	38.30	45.18	7.03	21.80	31.97
fPCG_p12_GW_39	32.95	0.39	66.90	61.16	34.29	1.85	32.26	45.78	34.62	3.67	23.12	38.93	35.94	6.63	17.87	33.03
fPCG_p21_GW_39	29.19	0.40	58.29	66.69	29.89	1.70	29.14	52.31	30.24	3.62	20.21	44.77	31.76	6.48	15.89	38.97
fPCG_p25_GW_37	40.11	0.39	81.14	61.45	41.22	1.81	38.90	46.20	42.55	3.70	28.12	39.08	45.35	6.48	22.67	33.49
Average	**37.77**	**0.40**	**75.75**	**60.97**	**38.55**	**1.84**	**36.18**	**45.87**	**39.89**	**3.67**	**26.50**	**38.94**	**42.57**	**6.77**	**20.82**	**32.85**

The samples collected are of 10 seconds duration, and data were digitized with a sampling frequency of 333 Hz at 8-bits ADC. Obtained fPCG signals are first pre-processed, where normalization and segmentation are performed on the signal. In the normalization process, PCG data is normalized so that the values of all data sets are mapped between 0 and 1. In the segmentation step, the heart sound data are edited into different fixed-length segments (corresponds to the 3000 samples). Fig. 2 shows the original, reconstructed, and error signal of fPCG_p01_GW_36 by applying different compression techniques. Tables 1, 2, and 3 detail the compression performance of DCT, DWT, and FWHT applied on fPCG signals. The database (fpcgdb) exhibits approximately similar average performance in terms of CPR, MSE, QS, and SNR, irrespective of any number of signals chosen. Here, we have considered randomly 10 different fPCG signals for evaluation. The CPR, MSE, QS, and SNR (in dB) are calculated for different user-specified PRD (UPRD) values varying from 0.5 to 2.0. Fig. 3(a-d) shows the variations of CPR, MSE, QS, and SNR for different values of PRD. It can be observed from Fig. 3 (a-d) that MSE and SNR show no significant change but CPR and QS show variations when PRD varies from 0 to 2.2 in the case of all the three transform techniques. QS is observed to be high when UPRD = 0.5 for all three techniques, indicating that UPRD values should be low for good compression. There was an increase in CPR by 4.21%, 3.51%, and 3.56% when UPRD changes from 0.5 to 1, 1 to 1.5, and 1.5 to 2.0, respectively, and the overall increase in CPR is 11.72% for the total change of UPRD value from 0.5 to 2.0 in case of DCT as shown in Table 1. Similarly, an increase of 5.04%, 3.84%, and 4.77% is observed in CPR in case of DWT, and 2.06%, 3.47%, and 6.71% are observed while applying FWHT. The overall increase observed in CPR for DWT, and FWHT respectively, is 14.28% and 12.70%, as shown in Tables 2 and 3. We have compared the performance of the proposed approach with the work reported in [10]. From results presented in Tables 1 to 3, it can be noted that CPR is far better, around 40% in the case of FWHT than DCT and DWT. Also, FWHT overweighs DCT and DWT in terms of QS.

V. CONCLUSIONS

We have applied compression techniques such as DCT, DWT, and FWHT to compress fPCG signals in this work. Performance measures

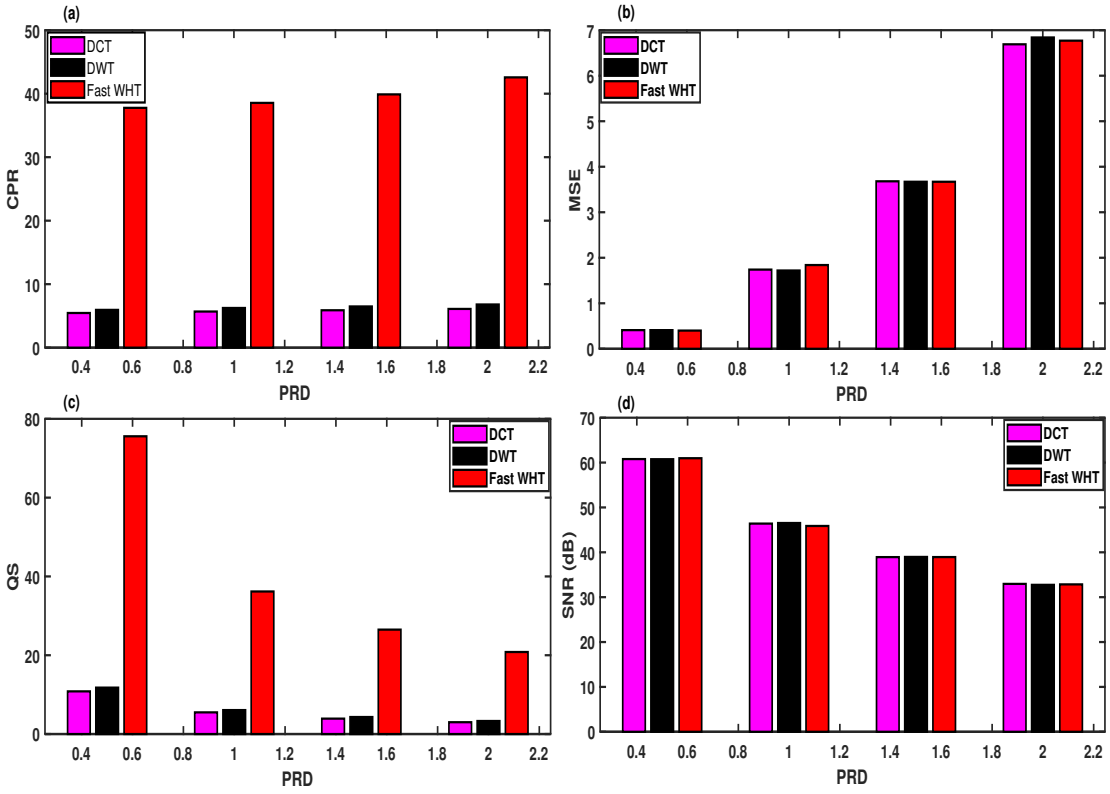

Fig. 3. (a) Compression ratio (CPR) versus PRD (b) MSE versus PRD (c) QS versus PRD (d) SNR (in dB) versus PRD

such as CPR, MSE, QS, and SNR are evaluated for each transform technique and a comparative study is performed. From the results, it is observed that FWHT is more robust than DCT and DWT and gives better compression performance, and preserves clinical information.

REFERENCES

[1] D. Mozaffarian, E. J. Benjamin, A. S. Go, D. K. Arnett, M. J. Blaha, M. Cushman, S. R. Das, S. De Ferranti, J.-P. Després, H. J. Fullerton *et al.*, "Heart disease and stroke statistics—2016 update: a report from the american heart association," *circulation*, vol. 133, no. 4, pp. e38–e360, 2016.

[2] V. A. B. K. Vadali, "A comparative study of signal processing methods for fetal phonocardiography analysis," 2018.

[3] M. S. Manikandan and S. Dandapat, "Wavelet energy based compression of phonocardiogram (pcg) signal for telecardiology," 2007.

[4] H. Habibzadeh, K. Dinesh, O. R. Shishvan, A. Boggio-Dandry, G. Sharma, and T. Soyata, "A survey of healthcare internet of things (hiot): A clinical perspective," *IEEE Internet of Things Journal*, vol. 7, no. 1, pp. 53–71, 2019.

[5] M. Elgendi, A. Mohamed, and R. Ward, "Efficient ecg compression and qrs detection for e-health applications," *Scientific reports*, vol. 7, no. 1, pp. 1–16, 2017.

[6] L. Yang, B. Zhang, and X. Ye, "Fast fourier transform and its applications," *Opto-Electronic Engineering*, vol. 31, pp. 1–7, 2004.

[7] C. K. Jha and M. H. Kolekar, "Electrocardiogram data compression using dct based discrete orthogonal stockwell transform," *Biomedical Signal Processing and Control*, vol. 46, pp. 174–181, 2018.

[8] M. Chowdhury, K. Poudel, and Y. Hu, "Phonocardiography data compression using discrete wavelet transform," in *2018 IEEE Signal Processing in Medicine and Biology Symposium (SPMB)*. IEEE, 2018, pp. 01–03.

[9] J. Martínez-Alajarín and R. Ruiz-Merino, "Wavelet and wavelet packet compression of phonocardiograms," *Electronics Letters*, vol. 40, no. 17, pp. 1040–1041, 2004.

[10] V. Aggarwal, S. Gupta, M. S. Patterh, and L. Kaur, "Analysis of compressed foetal phono-cardio-graphy (pcg) signals with discrete cosine transform and discrete wavelet transform," *IETE Journal of Research*, pp. 1–7, 2020.

[11] K. Ranjeet, A. Kumar, and R. K. Pandey, "Ecg signal compression using different techniques," in *International Conference on Advances in Computing, Communication and Control*. Springer, 2011, pp. 231–241.

[12] V. A. Allen and J. Belina, "Ecg data compression using the discrete cosine transform (dct)," in *Proceedings Computers in Cardiology*. IEEE, 1992, pp. 687–690.

[13] A. B. Roy, D. Dey, B. Mohanty, and D. Banerjee, "Comparison of fft, dct, dwt, wht compression techniques on electrocardiogram and photoplethysmography signals," in *IJCA Special Issue on International Conference on Computing, Communication and Sensor Network CCSN*, 2012, pp. 6–11.

[14] C.-Y. Pang, R.-G. Zhou, B.-Q. Hu, W. Hu, and A. El-Rafei, "Signal and image compression using quantum discrete cosine transform," *Information Sciences*, vol. 473, pp. 121–141, 2019.

[15] T. H. Chowdhury, K. N. Poudel, and Y. Hu, "Time-frequency analysis, denoising, compression, segmentation, and classification of pcg signals," *IEEE Access*, vol. 8, pp. 160 882–160 890, 2020.

[16] M. Subathra, M. A. Mohammed, M. S. Maashi, B. Garcia-Zapirain, N. Sairamya, S. T. George *et al.*, "Detection of focal and non-focal electroencephalogram signals using fast walsh-hadamard transform and artificial neural network," *Sensors*, vol. 20, no. 17, p. 4952, 2020.

[17] S. Sareen, S. K. Sood, and S. K. Gupta, "A cloud-based seizure alert system for epileptic patients that uses higher-order statistics," *Computing in Science & Engineering*, vol. 18, no. 5, pp. 56–67, 2016.

[18] A. A. Saraiva, F. Castro, N. J. C. Costa, J. V. M. Sousa, N. M. F. Ferreira, A. Valente, and S. Soares, "Comparative study of compression techniques applied in different biomedical signals." in *BIOSIGNALS*, 2019, pp. 132–138.

[19] K. Saka, Ö. Aydemir, and M. Öztürk, "Classification of eeg signals recorded during right/left hand movement imagery using fast walsh hadamard transform based features," in *2016 39th International Conference on Telecommunications and Signal Processing (TSP)*. IEEE, 2016, pp. 413–416.

[20] D. A. Huffman, "A method for the construction of minimum-redundancy codes," *Proceedings of the IRE*, vol. 40, no. 9, pp. 1098–1101, 1952.

[21] H. Tanaka, "Data structure of huffman codes and its application to efficient encoding and decoding (corresp.)," *IEEE transactions on information theory*, vol. 33, no. 1, pp. 154–156, 1987.

[22] Cesarelli, Mario and Ruffo, Mariano and Romano, Maria and Bifulco, Paolo, "Simulation of foetal phonocardiographic recordings for testing of FHR extraction algorithms," *Computer methods and programs in biomedicine*, vol. 107, no. 3, pp. 513–523, 2012.